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The impact of biomass consumption on CO_2 emissions: Cointegration analyses with regime shifts

Faik Bilgili *

Department of Economics, Faculty of Economics and Administrative Sciences, Erciyes University, Kayseri 38039, Turkey

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ABSTRACT

The source of carbon dioxide (CO_2) emissions has been of great interest to researcher(s) and/or policy maker(s) within ongoing efforts to diminish the emissions in the world due to CO_2's serious adverse environmental effect. This paper investigates the possible existence of long run relationship between CO_2 emissions and biomass consumption in US for the period January 1990–September 2011. To this end, paper first seeks for effect of biomass on CO_2 through energy literature and later follows cointegration analyses with structural breaks to reveal parameter estimates of long run equilibrium of CO_2 with fossil fuel consumption and biomass consumption. Eventually this paper explores that structural breaks are important to understand the course of CO_2 and that, as expected, fossil fuel and biomass effect CO_2 positively and negatively, respectively. Alternative cointegration analyses with regime shifts confirm negative impact of biomass and positive impact of fossil fuel on CO_2, as well.

Contents

1. Introduction

Throughout energy literature, one may observe that most concern has centered on main factors compounding the greenhouse gas (GHG) emissions. EREC [1] announces that carbon dioxide (CO_2) has the biggest share of GHG emissions and hence the biggest contributor to global warming having serious impact on environmental, social and economic costs.

The CO_2 emissions are the most important cause of global warming and therefore energy literature mainly focuses on reasons and causes of CO_2 emissions. What are the possible main contributors to CO_2 emissions? Coal is responsible for 30%–40% of world CO_2 emissions from fossil fuels and sulfur dioxide (SO_2) and NO_x contributes to acid rain as indicated in Omer [2], Dinçer [3], Kaygusuz [4] and Demirbas [5]. Diakoulaki et al. [6] employ Laspeyres model for Greece and reach the conclusion that electricity generation to the final demand, residential and tertiary sectors are the main contributors to continuous increase in CO_2 emissions. Omer [2] considers buildings the major source of final demand for energy. Cellura et al. [7] conduct structural decomposition analyses in Italy and state that main responsible for CO emission is eventually total final demand for goods and services. Acaroglu and Aydogan [8] claim that the usage of fuels, except biofuels, is the main explanatory factor of air pollution and acid rain problems. Kaygusuz [4] considers CO_2 and CO main variables to explain GHG and argues that 50% of anthropogenic greenhouse effect comes from CO_2.

Is there any target for CO_2? EU Committee [9] announces the target that EU will have 20% reduction at CO_2 emissions and 20% usage of final energy consumption from renewables by 2020. Is this target supported by estimations? EREC [1] indicates that biomass is expected to contribute half the 20% renewable target. Kaygusuz [10] foresees that fossil fuels meet 80% of global energy demand in 2008 and will be corresponding to 78% of global demand in 2030.

Do renewable reduce CO_2? EREC [1] reports that CO_2 emissions reduced from 1990 to 2009 by 7%, in EU, which corresponds to 340 million tones, through the use of renewable energy. Diakoulaki et al. [6] reach the outcome that the increase in usage of natural gas and renewable energy in the electricity sector causes CO_2 to

* Tel.: +90 5333765879; fax: +90 3524375239.
E-mail addresses: faikbilgili@gmail.com, fbilgili@erciyes.edu.tr

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reduce by approximately 9000 kt of CO_2 in Greece within examined period.

Is biomass efficient? Or, can biomass reduce CO_2? Berglund and Börjesson [11] affirm that the necessary energy input to produce energy through large-scale biogas plants corresponds to 20%–40% of the energy content in the biogas produced. They, however notice that biomass's positive net output of energy production becomes negative when transportation distance exceeds some distances. Fischer et al. [12] measure the productivity of biomass in EU and conclude that energy efficiency of biomass vary between EU countries depending on land use efficiency and 1st or 2nd generation feedstock and sustainability of feedstock. Acaroglu and Aydogan [8] emphasize the positive role of biofuels in mitigating the CO emissions although biofuels production from vegetable oils, animal fats and energy crops has still considerable costs. Khanna et al. [13] observe that the 5.5% of electricity from coal-fired power plants can be generated through a conversion of less than 2% of cropland to bioenergy crops and that this conversion mitigates CO_2 by 11% in Illinois since last fifteen years. Reinhardt and Falkenstein [14] compare the efficiency of biofuels and fossil fuels and they conclude that, although biofuels have some negative effects on environment, in terms of energy savings and GHG criteria, the biofuels are favorable in comparison with their fossil alternatives. Efficiency of bioenergy depends on largely the cost of production of it. Khanna et al. [13], Rogers and Brammer [15] notice the potential cost of energy conversion from biomass. The cost of energy production from biomass is twice the cost of energy production from coal (Khanna et al. [13]). Although biomass has barriers in terms of production cost and conversion efficiency (IEA, [16]), it is considered extensively for transportation sector (Sagar and Kartha [17], Grahn et al. [18]) and for production of electricity (Bauen et al. [19], Khanna et al. [13]). One may see also other seminal works focusing on biomass's substantiality through its ecological and economic effects as in Paine et al. [20], Caputo et al. [21], Radetzki [22] and Berglund and Börjesson [23].

The motivation of this paper derives from the research interest to observe if CO_2 emissions have long run relationship with biomass consumption. Therefore, this paper conducts cointegration (long run correlation) tests for CO_2 and biomass consumption by considering two possible structural changes through time. If result is in favor of cointegration, further, if cointegration parameter appears negative, then, policy makers may give more attention to biomass consumption to mitigate CO_2.

Accordingly, this paper mainly seeks for effect of biomass on CO_2, as some papers employed in this work do, but differs from those in terms of methodology. The originality of this paper hence is quantitative methodology of cointegration estimations with one and two unknown structural breaks. The next section explains methodology in details. Third section reveals the output from cointegration analyses and finally conclusion and recommendation section aims at providing researcher and policy maker with information about significance and magnitude of biomass consumption on CO_2 emissions.

2. Estimation methodology

The parameters of long-term relationship between macroeconomic variables have been always great interest to researchers. In order for a researcher to reach Gauss–Markov statistical properties and/or best linear unbiased estimators (BLUE), through his/her research, one of two following statistical conditions should be met. Either (i) the variables in regression individually are ought to be integrated of order zero [$I(0)$], or, (ii) individual series might be $I(1)$ in levels, but, then, they need to have at least one linear combination among themselves following stationary process [$I(0)$]. Throughout empirical evidences, the series of interest are found often $I(1)$. Therefore, in case series are not stationary in their levels, or, in other words, if they are I(d), where $d \neq 0$, one needs to detect if series are cointegrated before obtaining the parameter estimates from regression model. Otherwise traditional t, Wald and/or F statistics might produce biased and/or inefficient output. To this end, seminal cointegration works of Engle and Granger [24], Johansen [25] and Johansen and Juselius [26] have been employed intensively in the literature of economics and/or energy. Engle and Granger [24] run unit root tests for OLS residuals whereas Johansen [25], Johansen and Juselius [26] conduct maximum likelihood estimations for eigenvalue and/or trace statistics. These cointegration methods however assume that long run parameters do not change over time.

Following the new methodology of cointegration tests, this paper considers long run equilibrium with structural breaks. Gregory and Hansen [27] employ cointegration tests with one regime shift, Hansen and Seo [28] apply cointegration tests with two regime shifts through threshold analyses and Hatemi-J [29], expanding Gregory and Hansen [27], conducts cointegration tests with two regime shifts (structural changes). Following Gregory and Hansen [27], one may show traditional notion of cointegration relationship by Eq. (1) and the cointegration tests with regime shift by Eqs. (2)–(5).

$$Y_t = c + B'X_t + e_t \tag{1}$$

where Y_t, c, B', X_t and e_t represent dependent variable at time t, constant, transpose of beta vector, X matrix of explanatory variables at time t and residual term at time t, respectively. If e_t term is $I(0)$, then Y_t, and X_t are said to be cointegrated. However, this type of cointegration analysis assumes that both c and B terms do not change over time. Under this consideration, the cointegration tests would yield biased results, if in fact, the true data generating process experiences shift(s) in either c and/or B through long term time interval. Hence, Gregory and Hansen [27] add a dummy variable into Eq. (1) to capture possible regime shift as indicated by Eq. (2).

$$\delta_{t\tau} = \left\{ \begin{array}{lll} 0 & \text{if} & t \leq \lceil \eta\tau \rceil \\ 1 & \text{if} & t > \lceil \eta\tau \rceil \end{array} \right\} \tag{2}$$

where $\delta_{t\tau}$, τ and $[\eta\tau]$ refer dummy variable at time t, time break (change point within time interval) and integer part, respectively. Then Eq. (1) and Eq. (3) denote Model 1 and Model 2, respectively, where the later one employs additionally the possibility of change in constant (level). Therefore, Model 2 is also called a level shift model (C). Then Eqs.(4) and (5) indicate Model 3 considering shifts in level and trend (C/T) and Model 4 employing shifts in level and cointegrating slope coefficients (C/S), respectively, as is explained in Gregory and Hansen [27].

$$Y_t = c_0 + \delta_{t\tau} c_1 + B'X_t + e_t \tag{3}$$

$$Y_t = c_0 + \delta_{t\tau} c_1 + \varphi t + B'X_t + e_t \tag{4}$$

$$Y_t = c_0 + \delta_{t\tau} c_1 + B_0'X_t + B_1'X_t\delta_{t\tau} + e_t \tag{5}$$

Accordingly, c_0, c_1, B_0' and B_1' denote constant before regime shift, change in constant at the time of shift, transpose of cointegration slope coefficient vector before shift and transpose of cointegration slope coefficient vector at the time of shift, respectively.

Hatemi-J [29] extends cointegration tests of Gregory and Hansen [27] by following the possibility of two unknown regime

shifts instead of one unknown break. The dummy variables representing time break 1 (regime shift 1) and time break 2 (regime shift 2) are given by Eqs. (6) and (7).

$$\delta_{t\tau 1} = \left\{ \begin{array}{ll} 0 & \text{if} \quad t \le \lceil \eta\tau 1 \rceil \\ 1 & \text{if} \quad t > \lceil \eta\tau 1 \rceil \end{array} \right\} \tag{6}$$

$$\delta_{t\tau 2} = \left\{ \begin{array}{ll} 0 & \text{if} \quad t \le \lceil \eta\tau 2 \rceil \\ 1 & \text{if} \quad t > \lceil \eta\tau 2 \rceil \end{array} \right\} \tag{7}$$

$$Y_t = c_0 + \delta_{t\tau 1} c_1 + \delta_{t\tau 2} c_2 + B' X_t + e_t \tag{8}$$

$$Y_t = c_0 + \delta_{t\tau 1} c_1 + \delta_{t\tau 2} c_2 + \varphi t + B' X_t + e_t \tag{9}$$

$$Y_t = c_0 + \delta_{t\tau 1} c_1 + \delta_{t\tau 2} c_2 + B'_0 X_t + B'_1 X_t \delta_{t\tau 1} + B'_2 X_t \delta_{t\tau 2} + e_t \tag{10}$$

where c_0, c_1, c_2, t, B', B'_0, B'_1, B'_2 and e_t refer constant (level) term before regime shift, change in constant term at the time point of shift 1, change in constant term at shift 2 time, trend, transpose of cointegrating slope coefficient vector, transpose of cointegrating slope coefficient vector before regime shift, change in transpose of cointegrating slope coefficient vector at the time of shift 1, change in cointegrating slope coefficient vector at the time of shift 2 and residual term at time t, respectively. Accordingly, Eqs. (8)–(10) represent Model 2 (C), Model 3 (C/T) and Model 4 (C/S), respectively. In a cointegration equation in which fuel consumption (fuelcons) and biomass consumption (biomcons) are employed as explanatory variables, the Model (C/S) can be rewritten as in Eq. (11).

$$\begin{aligned} CO_{2,t} = {} & c_0 + \delta_{t\tau 1} c_1 + \delta_{t\tau 2} c_2 \\ & + B'_0 (fuelcons)_t + B'_1 (fuelcons)_t \delta_{t\tau 1} + B'_2 (fuelcons)_t \delta_{t\tau 2} \\ & + B'_0 (biomcons)_t + B'_1 (biomcons)_t \delta_{t\tau 1} + B'_2 (biomcons)_t \delta_{t\tau 2} + e_t \end{aligned} \tag{11}$$

One may follow alternatives of Eq. (11), as well. Related test statistics and parameter estimations of all equations are to provide researcher with information (i) whether or not CO_2 emissions, fossil fuel consumption and biomass consumption have long run relation (cointegration) through possible structural changes, (ii) if biomass consumption has significant and expected (negative) affect on CO_2 emissions considering possible structural changes within cointegration relation. The next section employs related data and cointegration analyses to obtain the information regarding (i) and (ii).

3. Data and empirical evidence

US monthly data for total energy CO_2 emissions, total fossil fuel consumption and total biomass consumption is obtained from EIA [30] and spans from January 1990 to September 2011. Table 1 shows descriptive statistics of related variables.

Table 1
Descriptive statistics of CO_2 emissions, fossil fuels consumption and biomass consumption in USA for the period January 1990–September 2011.

	Total CO_2 (Billion metric tons)	Fuel consumption (Quadrillion Btu)	Biomass consumption (Quadrillion Btu)
Mean	0.465662	6.713414	0.264290
Median	0.463243	6.680206	0.256622
Maximum	0.558109	8.109111	0.379876
Minimum	0.387747	5.590262	0.178544
Std. deviation	0.038493	0.568765	0.043341
Observations	261	261	261

Table 1 reveals that the expected values (means) of total CO_2, fuels consumption and biomass consumption are 0.465662 (billion metric tons), 6.713414 (quadrillion btu) and 0.264290 (quadrillion btu), respectively. Under normality assumption, 68% of CO_2 emissions' observations are within one standard deviation of mean (0.465662 ± 0.038493) and 95% observations of CO_2 cluster within 0.388676 and 0.542648. The 68% and 95% of fuel scores are observed within 6.713414 ± 0.568765 and 6.713414 ± 1.13753, respectively. About 68% of biomass consumption ranges from 0.220949 to 0.307631 and about 95% of biomass series scatter within interval from 0.177608 to 0.350972. Finally, one may notice also that the biomass consumption has relatively higher variance than CO_2 has.

Paper next determines the order of integration by Augmented Dickey–Fuller (ADF) tests and applies cointegration analyses. Although the major consideration is to investigate a possible impact of biomass on CO_2, to avoid from specification error in long run equilibrium model, fuels consumption is employed into model as independent variable as well as biomass consumption to explain CO_2 movements.

Table 2a, 1st column lists level and differenced variables to be tested. The 2nd, 3rd and 4th columns show tests statistics for ADF equation with constant, ADF equation with constant plus linear trend and ADF equation without constant and without trend, respectively. The relevant t statistics and probability values of t statistics in parentheses are introduced in the table. All three ADF equations' statistics indicate that CO_2, fossil fuel consumption and biomass consumption series individually have unit root. The null hypotheses that series have unit root are not be able rejected at 1%, 5% and 10% level of significances. On the other hand, the first differences of CO_2, fossil fuel consumption and biomass consumption are found stationary according to all three ADF equations. In other words, the hypotheses of unit root are rejected for each differenced series at 1%, 5% and 10% levels.

In Table 2b, first column gives dependent variable of the cointegration equation in which other two variables are explanatory. The second, third and fourth columns reveal Engel-Granger (EG) single equation constant (level) cointegration test, EG single equation linear trend cointegration test and EG single equation quadratic trend cointegration test, respectively.

Tau statistics and probability of tau statistics in parentheses are given in the table. All statistics from all three equations for each single equation EG indicate that series are not cointegrated. The null of no cointegration for each single EG is not able rejected at 1%, 5% and 10% level of significances. Therefore, throughout traditional cointegration analyses, one may conclude that there is no significant impact of biomass consumption on CO_2. At this point one may be worried if data has structural break(s) that EG cointegration tests did not capture. To this end, paper carries out cointegration tests with structural breaks (regime shifts), as well. Table 3 yields results of regime-switching cointegration analyses. In upper part of Table 3, the second, third, fourth and fifth columns give estimated cointegration parameters according to Hatemi-J (C/S), Gregory–Hansen (C/S), Hatemi-J (C/T) and Hatemi-J (C) models, respectively. In below part of Table 3, ADF and Phillips tests reveal cointegration tests (t, Z_t and Z_a) and structural break points. Finally, at the bottom part of Table 3, the goodness of fit statistics is available to be able to compare which model fits data better than the others do. All statistical outputs of Table 3 are obtained through gauss codes of Hatemi-J [29] and Hansen [31] with some additional program lines. All Hatemi-J models implement cointegration analyses with two unknown regime shifts while Gregory–Hansen (C/S) model carries out cointegration analysis with one unknown regime shift in constant and parameters as is explained in methodology section.

Table 2a
ADF unit root tests.

Levels	ADF (constant)	ADF (constant and trend)	ADF (no constant, no trend)
Null: Series have unit root			
CO_2	−2.037035 (0.2709)	−1.436995 (0.8478)	0.475484 (0.8169)
Fuel consumption	−2.099474 (0.2452)	−1.498293 (0.8279)	0.591802 (0.8436)
Biomass consumption	1.355528 (0.9989)	−0.065686 (0.9952)	2.168419 (0.9930)
First differences			
CO_2	−4.137572 (0.0010)	−4.382104 (0.0028)	−4.101455 (0.0001)
Fuel consumption	−4.384918 (0.0004)	−4.628309 (0.0011)	−4.332963 (0.0000)
Biomass consumption	−6.833342 (0.0000)	−7.197228 (0.0000)	−6.493916 (0.0000)

Table 2b
EG single equation cointegration tests.

Dependent variable	EG (constant)	EG (linear trend)	EG (quadratic trend)
Null: Series are not cointegrated			
CO_2	−1.2072 (0.944)	−1.4745 (0.969)	−1.7422 (0.980)
Fuel consumption	−0.9827 (0.966)	−1.4195 (0.973)	−1.3847 (0.993)
Biomass consumption	1.3722 (1.000)	−0.8364 (0.994)	−1.7095 (0.982)

Table 3
Cointegration analyses with one and two unknown regime shifts, $y=CO_2$; x=fuelcons~biomcons.

Parameter estimates	Hatemi-J (C/S)	Gregory–Hansen (C/S)	Hatemi-J (C/T)	Hatemi-J (C)
c_0	0.026* (5.015)	0.008*** (1.882)	0.030* (6.846)	0.030* (7.440)
$c_{1(\delta_{\tau1})}$	−0.001 (−0.064)	0.015 (0.981)	−0.002*** (−1.683)	0.005* (5.946)
$c_{2(\delta_{\tau2})}$	0.015 (0.848)		0.002 (1.283)	0.002**** (1.627)
φ			0.000* (3.752)	
$B_{0(fuelcons)}$	0.064* (76.898)	0.067* (109.569)	0.066* (108.986)	0.065* (118.684)
$B_{1(\delta_{\tau1},fuelcons)}$	0.019 (1.219)	0.035* (2.878)		
$B_{2(\delta_{\tau2},fuelcons)}$	0.000 (−0.184)			
$B_{0(biomcons)}$	0.038 (0.748)	−0.003*** (−1.904)	−0.037* (−3.701)	−0.019** (−2.029)
$B_{1(\delta_{\tau1},biomcons)}$	0.001 (0.497)	0.006 (0.159)		
$B_{2(\delta_{\tau2},biomcons)}$	−0.084*** (−1.729)			
ADF				
t stat	−9.823*	−9.352*	−9.978*	−9.355*
AR lag	5.000	2.000	5.000	2.000
First break point (ADF)	0.490	0.678	0.184	0.693
Second break point (ADF)	0.559		0.701	0.693
Phillips				
Z_t	−7.611*	−7.092*	−7.578*	−7.471*
First break point (Z_t)	0.475	0.609	0.192	0.471
Second break point (Z_t)	0.559		0.701	0.701
Z_a	−102.454*	−92.185*	−101.564*	−98.750**
First break point (Z_a)	0.475	0.609	0.192	0.471
Second break point (Z_a)	0.559		0.701	0.701
Goodness of fit				
Log likelihood	1052.964	1021.294	1037.157	1046.459
Akaike	−10.891	−10.649	−10.770	−10.841
Schwarz	−10.864	−10.621	−10.743	−10.814
Hannan–Quinn	−26.299	−26.056	−26.178	−26.249

Notes: (1) The asterisks (*), (**), (***) and (****) represent the significances of 1%, 5%, 10% and 15%, respectively, (2) The values in parentheses are t statistics, (3) Hatemi-J models' null of no cointegration tests' asymptotic critical values for ADF t, Phillips Z_t and Z_a are obtained from Table 1 of Hatemi-J [29], (4) Gregory–Hansen model's null of no cointegration tests' asymptotic critical values for ADF t, Phillips Z_t and Z_a are obtained from Table 1 of Gregory and Hansen [27].

There are two immediate outcomes through cointegration analyses with structural breaks; (i) all four alternative models conducted in this paper reveal that CO_2 emissions are cointegrated with biomass consumption and fossil fuel consumption, (ii) all alternative models indicate that biomass consumption mitigates CO_2 emissions while fossil fuel consumption compounds it.

All of four models' ADF t, Z_t and Z_a, except Z_a of Hatemi-J (C), statistics indicate that CO_2 emissions are cointegrated with biomass consumption and fossil fuel consumption with 1% level of significances. Z_a of Hatemi-J (C) is significant at 5% level. Through these outcomes, one may emphasize the existence of a strong long run relation of CO_2 with fuel and biomass consumptions.

According to goodness of fit criteria, it appears that Hatemi-J (C/S) model is best and Hatemi-J (C) model is found second best among other models. The higher the log likelihood, the better the model is. Likewise the lower the Akaike, Schwarz and Hannan-Quinn, the better the model fits data.

Hatemi-J (C/S) estimations indicate that the constant term at time *t*, the coefficient of fossil fuel consumption at time *t* and the coefficient of biomass consumption at second structural break time point are found statistically significant on CO_2 emissions. The estimated significant coefficient of fossil fuel consumption implies that, as fossil fuel consumption increases by one quadrillion btu, the CO_2 emissions will increase by 0.064 billion metric tons, or, equivalently, 64 million metric tons. The estimated significant coefficient of second structural break of biomass consumption states that the impact of biomass on CO_2 becomes negative significantly at the second break time point with the value of 0.084 units and hence it takes the final value of -0.046 ($=0.038–0.084$) thereafter. Therefore, as biomass consumption rises by one quadrillion btu, the CO_2 emissions will decline by 0.046 billion metric tons (or 46 million - metric tons) during second regime.

A careful interpretation is necessary at this stage. Hatemi-J (C/S), following cointegration analyses with two structural breaks as given in Eq. (11), observes that the coefficient of biomass consumption on CO_2 emissions (0.038) is not significant until second regime shift. The coefficient becomes significant at second regime shift and takes the value of -0.046 after the time point of second regime shift until September 2011, which is the end of data employed in the paper. The overall conclusion is that fossil fuel consumption leads CO_2 emissions to increase whereas biomass consumption results in decrease in CO_2 emissions.

The second best model of Hatemi-J (C) model reveals negative impact of biomass consumption on CO_2, as well. The model yields statistically significant estimators for constant at time *t*, constant at the time of first regime shift and afterwards, fossil fuel consumption at time *t*, and biomass consumption at time *t*. The constant term at the time of second regime shift has a *t* value of 1.627. The two-tailed probability of the coefficient of 1.627 is 0.104967 with $df=256$. Therefore one may interpret that it is significant at 11%, rather than 0.10%, yet literature follows in general the percentages 0.01, 0.05, 0.10 and, when necessary, 0.15 and 0.20, respectively.

Overall one may claim that Hatemi-J (C/S) model captures second structural break of biomass consumption and that Hatemi-J (C) models captures first and second structural breaks of constant term in equation. Both models find negative sign of biomass consumption on CO_2 emissions. Gregory–Hansen (C/S) and Hatemi-J (C/T) models obtain negative statistically significant coefficients of biomass consumption on CO_2, as well. Among other statistically significant coefficients at time *t*, Gregory–Hansen (C/S) exposes first regime shift's coefficient of fossil fuel consumption, while Hatemi-J (C/T) picks out the coefficient of constant term at first regime shift.

The best, second best and other two, all of four models, consider possible structural change(s) in cointegration equation and produce the outcome that fossil fuel consumption has positive effect on CO_2 emissions whereas biomass consumption has negative effect on CO_2. According to three Hatemi-J [29] models, the long run positive impact of fossil fuel consumption on CO_2 ranges from 0.064 to 0.066. As for Gregory and Hansen [27] model in the table, it estimates the coefficient of fossil fuel as 0.067 till the first break and 0.102 ($=0.067+0.035$) after the break. Again, in terms of three Hatemi-J [29] models, the long run negative impact of biomass consumption on CO_2 spans from -0.019 to -0.046. On the other hand, Gregory and Hansen [27] model finds a negative value of 0.003 for biomass consumption's coefficient.

Eventually, according to goodness of fit measurements, one may consider mostly the Hatemi-J (C/S) output in evaluating the effect of fossil fuel and biomass on carbon emissions. The Hatemi-J (C/S) model underlines that second regime shift occurs on February 2002 and that the consumption of biomass becomes effective in reduction of carbon emissions during second regime period (March 2002–September 2011).

In an effort to explore the reasonable factors behind the second regime shift time of February 2002 in US, one may investigate possible energy shortages, environmental facts and/or environmental policies and/or renewable energy polices by US administration in 1990s and beginning of 2000s. Some energy dynamics in US such as the cumulative energy shortages in US until 2000s (Pimentel et al. [32]) and/or energy crises like California electricity crisis of 2001–2002 (Pope [33]) may have played some role in increasing the efficiency of energy production and consumption from biomass in US towards 2002. Or rather, in general, one may claim that US energy policies stimulated the biomass energy production within related period. US Energy Information Administration polices, EIA [34] indicates that, in 1990s, the most important law that promotes renewable energy, especially wind projects and biomass plants is Energy Policy Act (EPACT) of 1992. EPACT implements tax incentives for renewables from 1994 to 1999 and, by extending the period, EPACT is reimplemented in 1999 and 2001 until 2003 (EIA [34]).

4. Conclusion and policy recommendation

In this work, author attempts to reveal explicitly whether or not biomass consumption can mitigate carbon dioxide (CO_2) emissions. To this end, paper first follows literature evidence on carbon emissions and renewables. Among other renewable sources, biomass is given priority in the paper, since it, throughout the literature, has been a subject of ongoing discussions/researches to explore if biomass is efficient to reduce CO_2 emissions. Later paper employs cointegration analyses with one and two possible unknown regime shifts. This cointegration methodology challenges traditional cointegration works since traditional ones do not consider possible structural breaks and hence they may fail to produce unbiased and efficient estimations. Employing US monthly data from 1990:1 to 2011:11, this paper states that structural breaks (regime shifts) are essential to understand the long run equilibrium of CO_2 emissions with biomass consumption. In order for cointegration model to be specified well, besides biomass consumption, the fossil fuels consumption is also employed into model as an explanatory variable. Four alternative cointegration models result in positive impact of fuels' consumption and negative impact of biomass consumption on CO_2. Among others, the Hatemi-J (C/S) model fits the data best and observes biomass consumption's significant parameter of -0.046 during second regime period and fuel consumption's significant parameter of 0.064 during all data period. The second regime shift appears on February 2002. One can state that as biomass consumption increases one quadrillion btu, the CO_2 emissions will reduce by 0.046 billion metric tons (or equivalently 46 million metric tons) after February 2002 in US.

Throughout the findings of cointegration model considering two regime shifts at constant and parameters, this paper may suggest US Energy Administration keeping to update the Energy Policy Act (EPACT) of 1992 to diminish CO_2 emissions. Through the possible research and development expenditures on biomass plants, one may also expect that the magnitude of biomass's adverse effect on CO_2 may increase in US within next decade(s). This expectation of course depends upon the assumption that magnitudes of other parameters, such as population growth and growth in demand for energy, will not increase beyond the expectations.

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